

How Do Biotech Cluster Firms Catch Knowledge Spillovers? The Strong Impact Of The Institutional Mechanisms

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ABSTRACT

This paper deals with the nature of the mechanisms supporting knowledge spillovers diffusion in high-tech clusters. The literature in the geography of innovation focuses on the existence of local knowledge spillovers, which are enhanced by geographic and technological proximity. However, the mechanisms explaining the diffusion of spillovers are not well understood. If knowledge spillovers exist, how does this knowledge diffuse among the actors? Do spillovers spread in the air, as suggested by Marshall? Or, are there mechanisms that explain their dissemination?

Based on a firm survey data base and an original methodology, the paper explores the determinants of knowledge spillovers. The paper has twofold purposes; the first one is to determine the main mechanisms within a region enabling the diffusion of spillovers. The second objective is measuring the impact of these main mechanisms on firm's innovation performance, indicating which of these mechanisms are more effective in transporting knowledge spillovers between agents. The results show new empirical evidences on the role played by institutions¹ in the dissemination of externalities. However, informal mechanisms, such as face-to-face contacts commonly stressed in the literature, have no significant and negative effects in this case.

Keywords: Knowledge Spillovers; Diffusion; Innovation; Regional Cluster; Biotech

1. INTRODUCTION

*K*nowledge spillovers among firms or between firms and university have been studied since the seminal works of Jaffe, Trajtenberg and Henderson, 1993; Audretsch and Feldman, 1996; Paci and Usai, 2000, among others. Their empirical studies show that spillovers are localized in space and are technologically specific. However, the mechanisms of knowledge diffusion are not well understood as exemplified by the statement in Jaffe (1989: 957):

“There has been much recent interest in “spillovers” of research among firms (Jaffe, 1986). There is even more reason to believe that spillovers exist from universities to firms, since the former have less incentives to try to keep research secret... For none of these spillover phenomena are “the transport” mechanisms understood. If the mechanism is primarily journal publications, then geographic location is probably unimportant in capturing the benefits of spillovers. If however, the mechanism is in informal conversations, then geographic proximity to the spillover source may be helpful or even necessary in capturing the spillover benefit.”

There are few studies dealing with these topics. The existence of channels to diffuse knowledge spillovers is being assumed by authors who emphasize the role of face-to-face contacts that facilitate tacit and informal knowledge spillovers (Breschi & Lissoni, 2001). The present paper demonstrates that knowledge spillovers are not necessarily a

¹ Institutions are defined here as a kind of structures that matter in structuring social interactions (Hogdson, 2006). Institutions can enable or constraint choices and actions. So it can enhance agent behaviors and actions that otherwise would not exist. According to this definition, formal institutions supporting R&D and innovation activities of SMEs in the biotech industry can enable or constraint actions of these firms regarding accessibility to critical resources available in a given region such as knowledge, information, finance, etc. Finally, we can assume that Institutions structures can explain variation in regional innovation performance.

natural and a spontaneous process enhanced by face-to-face contacts. Based on panel data set of biotech firms in the Paris region areas, Ile-de-France (IDF), the next section provides a review of the literature on the main mechanisms enabling diffusion of knowledge spillovers. Section 3 presents the methodological issue used to make a typology of the main channels operating at the region. The results show that three factors are considered as main channels through which spillovers percolate at the regional level; institutions, communication, and codified data bases. Section 4 tests & measures the impact of these main channels on innovation. Strong evidences highlight the major role of the institutional structures sustaining R&D (research and development) and innovation in the region, as the transport mechanism of knowledge spillovers between agents.

2. MICRO FOUNDATIONS OF KNOWLEDGE SPILLOVER'S DIFFUSION

One idea that comes up quite often in the literature considers the contacts-face-to-face as the main mechanism of knowledge spillovers dissemination. However, little to not say any empirical evidences allows us to establish such conclusion (Breschi & Lissoni, 2001). Empirical studies deduce or assume the existence of knowledge spillovers without giving any measurable proofs to accept such assumptions.

The present paper aims to investigate the mechanisms transporting knowledge spillovers in a regional cluster. Given this research agenda, it is worth noting the contribution of the Urban Economics which gives a large interest to the human capital as a source and a mechanism of knowledge spillovers. Therefore, the qualification of individuals, their educational background and also the density agglomeration of people in cities can explain and generate more opportunities to exchange valuable information and knowledge (Duranton & Puga, 2004). However, this literature relies on aggregated data and is focused on the issue of “codified” knowledge (i.e. level of education or qualification). However, more recently, researchers interested in the tacit dimension of human capital spillovers at the micro geographical level suggests new insights of their diffusion and how do they improve innovation performance at the firm level. (Charlot & Duranton, 2004; Bayer, Ross & Topa, 2005; Shihe Fu, 2007; Rosenthal & Strange, 2008). Based on this recent literature, the paper discusses the role of three main channels of knowledge diffusion which are communication; labour mobility; and institutional embeddedness². The nature of the mechanisms used to capture spillovers by firms in regional clusters is investigated and the assumption of whether or not these channels impact the firm's innovation capacity is tested.

2.1 Communication

As already suggested, many models consider the density and the quality of human capital in knowledge dissemination. These models are based on the assumption that geographical concentration of skilled labour promotes socialization between those individuals by providing more opportunities to meet and thus increasing the probability for exchanging tacit knowledge (Shihe Fu, 2007). Her paper shows that human capital attenuates at different speeds over distances. For example, the effect of the depth of human capital decays rapidly three miles away from the centre. She concludes that knowledge spillovers are strongly localized within a micro geographic scope in cities which she refers to as “Smart café cities”. Similarly, Bayer, Ross and Topa (2005) find evidence of significant social interaction at the “block” level. More precisely, they find that the benefits of spatial concentration are driven by proximity to college educated workers and that these effects attenuate sharply with distance (between 5 and 25 miles). However, although these studies underline the importance of the density and quality of human capital in the dissemination of knowledge spillovers in a context of geographical proximity, the mechanisms involved in their diffusion are not identified explicitly but rather inferred. More insight on this aspect are provided by Charlot and Duranton (2004) who focus on the role of communication among workers, defining “communication externalities” as knowledge exchange stemming from face-to-face meetings, word-of-mouth communication, and direct interactions between skilled workers.³ Based on a survey of workplace communication among individual workers in French cities, the authors identify and measure the impact of “communication externalities”. They show that in larger cities with higher proportions of more educated population, workers communicate more, which, in turn, has a positive effect on wages. Charlot and Duranton show that 13 per

² Embeddedness refers here to firm's interaction with institutional agents.

³ For Charlot and Duranton (2004) human capital can have external effects through a variety of other channels. More human capital in a city could foster the supply of specialised intermediate goods and, in turn, improve the productivity of final producers or lead to better matches between employers and employees – a pecuniary externality unrelated to communication externalities.

cent to 22 per cent (depending on the estimates) of the effects of more educated population and larger city on wages diffused through communication.

Given these results, we can assume that communication among workers enhances knowledge and technological spillovers, which, in turn, stimulate the productivity of individuals leading to greater innovation. We therefore postulate proposition P1:

Proposition (P1): Communication and direct interaction among qualified employees both within and outside the company are channels through which knowledge is diffused among agents, which affects innovation.

2.2 Mobility of Labour

To what extent does the mobility of researchers, inventors and engineers promote the dissemination of knowledge spillovers? There are two strands of the literature studying these questions. The first strand investigates the determinants of labour mobility and its impact on the dissemination of knowledge spillovers. A rich literature have emerged discussing the importance of knowledge exchange between the public and the private sphere (Zucker, Darby & Torero, 2002; Zucker, Darby & Brewer, 1998; Crespi, Geuna & Nesta, 2006) or between firms (Rosenkopf & Almeida, 2003; Breschi & Lissoni, 2006 a, b). The main results to which conclude these studies suggest that if knowledge diffusion is local this is because researchers' and engineers' mobility is limited to the regional level space (Rosenkopf & Almeida, 2003; Singh, 2005; Breschi & Lissoni, 2006 a, b, 2009). In addition, these studies show that the role of social networks is crucial for accessing local capital stock (Breschi & Lissoni, 2006b) and that knowledge flows are indeed inter-related with mobility of researchers regardless of their geographical proximity (Rosenkopf & Almeida, 2003, Breschi & Lissoni, 2006a). These results suggest finally, that the effects of co-localization between cited and citing patents tend to diminish if the patents in question are not bound by a network.

In conclusion, it should be noted that the above results highlight the importance of human capital mobility as a mechanism for dissemination of knowledge but do not measure the impact on firm productivity or innovation. This question is of interest since in high-tech clusters the problem of poaching is widespread and the business activities of firms can be driven by the intensity of employee turnover. This raises questions about the relationship between researcher mobility, employee poaching and entrepreneurial innovation. So, when and how can mobility be considered as a means of positive knowledge spillover?

The second strand of the literature focuses on the relationships between the mobility of the workforce and firm's performance in clusters. Duranton and Puga, (2004), for example, show that poaching of "strategic employees" is a commonly accepted occurrence that aims at appropriating tacit knowledge. However, Combes and Duranton (2006) argue that firms can miss their target which is benefit from the economies of agglomeration (i.e. availability of labour and better matching between employers and employees), because firms in clusters can face a trade-off between the benefits (access to knowledge) and disadvantages (higher wages) of proximity to the labour market. Thus, companies derive less benefit from co-location if the costs of co-location outweigh the advantages. Fosfuri and RØnde (2003) consider that firms are encouraged to cluster under certain conditions like the possibility of rapid technological progress and a weak competition on the product market.

This suggests that mobility of labour, although it may be a channel for knowledge diffusion is not a sufficient condition to increase innovation in firms. We therefore postulate proposition P2.

Proposition (P2): Higher employee turnover in one firm leads to lower knowledge accumulation, higher costs of production and lower levels of innovation.

2.3 Institutional Embeddedness

The third issue discussed in the literature is the impact of institutional embeddedness as a channel for knowledge spillovers. In the social network economics literature, the concept of embeddedness appears with the seminal studies of Granovetter (1973; 1985) and White and Harrison (1992), suggests that new information is obtained mainly through

relationships with not closely connected network agents, i.e. through “weak ties”. But in the context of innovation, this interpretation is less obvious because the connectivity of one agent to a given network, whether it is “strong” or “weak”, depends on the characteristics of the knowledge being transferred (Fritsh & Kauffled-Monz, 2010). In addition to social ties, the authors highlight the importance of regional embeddedness as a means of knowledge transfer between agents. So, if a region is endowed with talent and critical resources, specific mechanisms such as public structures or formal institutions, playing the role of brokers, allow bridging between agents and enhance communication. In a context of regional clustering, the institutional embeddedness of firms - i.e. having “strong” and/or “weak” ties with “institutional broker agents” can shape agents’ actions by fostering the search for new business opportunities, and research and development (R&D) activities, etc. Grossetti (2000) refers to this mechanism as mediation resources, considering that networks play the role of operators that facilitate access to information and knowledge. This is true when agents are bounded rationality (Simon, 1959). Then, their ability to create business or innovative activities is determined by their capacity to activate two kinds of critical resources: 1- relational (with customers, suppliers, researchers, consultants); and 2- mediation, through interactions with organizations and institutions of formal innovation (Bouba-Olga & Grossetti, 2007). However, the differentiation between the two levels of analysis is not obvious, and few studies attempt to disentangle the concept or provide any empirical evidence.⁴ The more general concept of “entrepreneurship capital”, is used in the literature to capture these aspects. Audretsch and Keilbach (2004) refer to entrepreneurship capital as the capacity for geographically relevant spatial units of observation to generate the startup of new enterprises. Whereas for Egbert (2009) entrepreneurship capital is rather reflecting a number of legal, institutional, and social factors and forces that create the capacity for entrepreneurial activity.

In this sense, entrepreneurship is considered to be a mechanism that converts economic knowledge (*via knowledge spillovers*) to economic growth (Braunerhjelm, Audretsch & Carlsson, 2010). And the ability of regions to develop the entrepreneurship capital needed to enhance venture creation explains a large part of the variation in economic growth between regions.

At the firm level, it seems important to evaluate the firm’s capacity to activate and use resources in a given regional space. In this sense, not only the traditional factors of production are considered such as labor and capital but rather the combination with complementary factors:

1. The regional endowment with institutional devices (formal public/private organizations sustaining innovative activities of firms; financial, associational or incubation, etc.);
2. The degree to which agents turn to these institutions to capture and exploit information, knowledge and services to achieve their innovation activities.

Therefore, we can postulate assumption P3.

Proposition (3): Stronger institutional embeddedness of firms (i.e. through interaction with institutional agents) leads to more opportunities for capturing knowledge spillovers and increases innovation.

3. DATA AND TYPOLOGY

Drawing on this framework, the paper measures the impact of enhancing knowledge spillover of one region. The task is then achieved in two steps. First, channels operating as conducts for knowledge spillovers in a given region are identified. Particularly, in the case of the biotech industry, a rich and a diversified institutional infrastructure govern knowledge flows (Kaiser & Liecke, 2008; Owen-Smith & Powell, 2004; Boufaden, Lourimi & Torre, 2010⁵). Second, a typology of the main channels is drawn. The results of the qualitative analysis show that three factors can be considered as main channels through which spillovers can percolate at the regional level; institutional agents, communication, and codified data bases. But only the institutions sustaining firm’s innovation activities like chambers of commerce, incubators, and associations, actively participate in knowledge and information diffusion.

⁴ See the discussion in section 4.

⁵ See the paper for more details on the institutional design of the biotech industry in Ile-de-France.

3.1 Sample

The empirical analysis is based on firm data collected between 2004 and 2005 using a unique designed questionnaire. These data were collected at the business unit level. A first sample was identified by integrating four distinct professional and public directories.⁶ It included 244 firms (biotechnology firms, users of biotechnology, suppliers and consulting) from which we retained 107 firms located in the Ile-de-France region and that used or produced biotechnologies in their R&D processes. A survey questionnaire was sent to them and additional data were gathered by phone and/or direct interviews between June 2004 and July 2005; 71 firms responded, but data are from only 60 of these due to missing data. The final sample represents 56% of the population of the biotechnology firms in Ile de France region. However, we believe that the sample is representative regarding the age distribution of firms and their specialization (Table 1).

Table1. Representativeness of the sample at regional level

Age of the firms	Population (Region)		Sample (Survey)	
0-2 years	36	33%	20	31%
3-5 ans	30	28%	23	36%
6-10 ans	18	17%	10	16%
10 ans et plus	22	20%	11	17%
Age inconnu	3	3%		
Total	109	100%	64	100%

Data for 2003

Also, comparison with the *OECD Biotechnology Statistics* (2006)⁷ gives some indication about the representativeness of the sample compared with French core biotechnology firms⁸ (Table 2). Our sample slightly overestimates small firms (67% of the sample compared to 58% for the French core biotechnology firms) but slightly underestimates firms with 20 to 49 employees (13% compared to 21%). Regarding the level of R&D spending, our sample is representative for firms with fewer than 20 employees (346 000 € compared to 334 000 €) and for average levels of R&D spending across all firms (2423 € compared to 2612 €). It is less representative for medium sized firms (20-49 and 50-249 employees) for which R&D spending is twice as high in our sample as in the French population of firms. Consequently, caution is needed in interpreting the results (Table 2).

Table 2. Representativeness of the sample at national level

Size	French core biotechnology firms* (458) **		Sample firms performing R&D activities in the region (60) ***	
	% of the R&D biotech firms	Average of R&D expenditure by firm in K €	% of the R&D biotech firms	Average of R&D expenditure by firm in K € in €'000
< 20	58 %	334	67%	346
20-49	21 %	1,382	13%	2,824
50-249	14 %	3,536	13%	8,872
250-499	3 %	10, 687	0 %	-
> 500	1 %	62, 255	5%	11,167
Total	100%	2,612	100%	2,423

Source: Data for 2003

(*): Core biotechnology firms are firms with more than 75% of their R&D expenditure on biotech applications.

(**): 458 firms are listed in the R&D survey of the Ministère de l'Éducation Nationale, de la Recherche et de la Technologie, November 2005, in *OECD Biotechnology Statistics* (2006). <http://www.oecd.org/dataoecd/51/59/36760212.pdf>

(***): 60 firms in the sample

⁶ Biotechnologies France, Adébio, Génopôle d'Evry and France Biotechnologie.

⁷ <http://www.oecd.org/dataoecd/51/59/36760212.pdf>.

⁸ French core biotechnology firms devote 75% of their R&D budgets to biotechnology activities and best represent our population of firms.

Finally, in terms of sample characteristics the distribution of firm size is skewed; nearly half of the firms in our sample are micro-companies (less than 9 employees). Table 3 presents four age-classes with the average number of total R&D employees and their R&D spending. To summarize, firms are small sized and very heterogeneous in terms of R&D employees and R&D spending.⁹

Table 3. Sample firm characteristics

	Average	Median	Minimum	Maximum
Date of creation	1994	1999	1872	2003
Total employees	59	14	1	950
Age of the firm (year)				
0-2	13	5	1	115
3-5	58	18	1	858
6-10	37	11	1	116
>10	169	23	1	950
R&D employees	19	6	1	132
Age of the firm (year)				
0-2	10	4	1	95
3-5	17	9	0	132
6-10	17	4	0	92
>10	10	12	1	14
R&D budget (K €)	2303	285	2637	23000
Age of the firm (year)				
0-2	1.796	225	0	23.000
3-5	2.705	1.091	0	17.653
6-10	2.646	155	45	17.333
>10	2.046	224	0	14.148

Data for 2003

3.2. Classification (PCA)

A principal component analysis (PCA) classifies different mechanisms into groups of variables or “factors” that condense similar information (Hair, Black, Barbin & Aderson, 1998)¹⁰.

Top managers and R&D unit directors of the sample’s firms were asked to indicate the importance of the use of different channels to access knowledge or information for their economic watch. The PCA reduces the list of variables. This procedure is necessary before proceeding to an econometric application testing the impact of the main mechanisms on firm’s capacity to innovate.

Respondents were asked whether their firms use the following diffusion mechanisms within or outside the region Ile-de-France: firm employees (INTRA), universities/public research labs (UNIV), government/national organisms supporting firm activities (OSEO, CDC, etc.) (MINS), regional and departmental organizations and institutions (INST), associations (ASSOC), clients-suppliers (CLI-SUPP), firm’s services and consultants (CONS), Top managers and researcher’s interactions (MAN-RES), conferences and exhibitions (CONF), professional training (TRAI), scientific publications (PUBLI), patents (PAT). These variables are specified at five response levels, ranging from 5 most important sources of information for economic watch activities, to 1 least important. Corresponding binary variables are then introduced.

The PCA is performed using Stata procedure and the rotation orthogonal factors (VARIMAX). Three main factors emerge from this analysis (see tables 4a and 4b). The results show that these variables are clearly distinguishable from each “principal factor”. The three main factors are *communication*, *institutions*, and *data bases*.

⁹ In order to fund their R&D activities, the firms in our sample diversify their sources of finance: 29% of firms benefit from capital venture and 14% from business angels. The others rely mainly on public funding through subsidies and grants.

¹⁰ We do not present the PCA procedure since it is a preparatory stage only for the econometric analyses. The results are available upon request.

Table 4a. Principal-Component-Factor-Analysis

Factor analysis/ correlation	Number of obs = 220
Method: principal-component factors	Retained factors = 3
Rotation: orthogonal varimax (Horst on	Number of params = 33

Factor	Variance	Difference	Proportion	Cumulative
Factor1	2.78148	0.31331	0.2318	0.2318
Factor2	2.46818	0.37334	0.2057	0.4375
Factor3	2.09484		0.1746	0.612

LR test: independent vs. saturated: $\chi^2(66) = 1046.93$ Prob> $\chi^2 = 0.0000$

Table 4b. Rotated factor loadings

Rotation: orthogonal VARIMAX

Variable	Factor1	Factor2	Factor3	Uniqueness
INTRA	0.3571	0.1415	0.4747	0.6271
UNIV	0.5504	0.3825	0.2167	0.5038
MINS	0.0381	0.857	-0.1114	0.2518
INST	0.1444	0.8467	0.0603	0.2586
ASSOC	0.0431	0.6682	0.5569	0.2416
CLI-SUPP	0.7778	0.2572	0.1096	0.3169
CONS	0.336	0.481	0.3225	0.5517
MAN-RES	0.625	0.1968	0.2436	0.5113
CONF	0.7231	0.045	0.3623	0.3438
TRAIN	0.7607	-0.1335	0.1217	0.3886
PUB	0.2938	-0.1479	0.7719	0.296
PAT	0.1744	0.1619	0.761	0.3643

Factor 1: Communication

Communication reflects the importance of informal discussions with customers and suppliers, employees, researchers and managers during training, at conferences or in informal meetings.¹¹ This factor indicates the ability of employees to seek the information needed to perform their activities and to solve specific problems according to the definition of Charlot and Duranton (2004). These variables measure the ability of employees (researcher or manager) to extract information and tacit knowledge from face-to-face contacts. This requires individuals meeting up, exchanging ideas and socializing in different contexts, e.g. conferences and training with researchers or engineers specialized in the same areas. Von Hippel (1987) considers these opportunities as determinants for people trying to build up their professional networks to exchange ideas and find solutions to problems they encounter at work. Thus, communication is a mechanism that allows the diffusion of tacit knowledge and human capital spillovers.

Factor 2: Institutions

This factor considers the institutional agents involved in the dissemination of scientific, technological and economic knowledge. Three variables are involved: government/national/regional business organization support such as OSEO (French Institution supporting the growth of SMEs), CDC (Caisse de Dépôts et Consignation); and professional associations such as France Biotechnology and Club Alpha. However, it should be noted that this factor may reflect access to information rather than knowledge for firms seeking specific sectoral resources, partners and various devices available to help managers to initiate and develop their activities. In this category of agents, chambers of commerce were rated highly by the companies in our sample for helping finding partners for co-development or marketing of their products. Associations such as France Biotechnology or Club Alpha play an important role by organizing regular meetings between heads of companies and professionals such as corporate venture capitalists. Grossetti (2000) calls these institutional agents the “mediation resources”.

¹¹ Note that universities and public/private research labs are ranked 5th which helps to explain the low score for the first factor: to ensure maximum variance between factors we decided not to include it.

Factor 3: Data bases

Two variables explain this last factor: academic and scientific specialized publications and patents databases. This factor reflects the stock of codified knowledge available to researchers and entrepreneurs (Jaffe, 1989). Access to these databases is easy and generally freely available on the Internet.

4. MECHANISMS AND THEIR IMPACTS ON DIFFUSION OF SPILLOVERS AND INNOVATION

After identifying the main channels of knowledge spillovers operating at the regional level, the second step in consists at measuring these channels's impact on firm innovation. In the geography of innovation literature, the knowledge production function (Griliches, 1979) allows testing such relationship. So which kind of mechanisms enhances significantly the diffusion of spillovers? Are spillovers in the air and spread through communication or in the contrary need some established formal mechanisms to be caught by agents? In the same time it seems important to investigate the extent to which firm's innovation is driven by local knowledge spillovers.

Using the database described above and the knowledge production function (Griliches, 1979), the paper test the importance of the different mechanisms allowing knowledge and information diffusion among the firms and actors in the cluster. Therefore two dependent variables are specified: the annual patent application and the number of R&D projects in the firm's pipeline. The first model characterizes the firm's exploration or search strategy which allows for continuous innovation and knowledge exchange and combination. The second model indicates an exploitation and business strategy for production and delivery of firms' products and services.

Table 5. Descriptive statistics

Variables	Mean	S.D.	Min	Max
Patent	1.486	3.248	0.000	20.000
prod_pipeline	4.705	8.029	0.000	52.000
Age	9.918	22.270	0.000	133.000
Spinoff	0.673	0.470	0.000	1.000
Health	0.727	0.446	0.000	1.000
Size>20	0.777	0.417	0.000	1.000
L R&D expend	5.648	2.347	0.000	10.043
L R&D employees	1.493	1.051	0.000	4.890
R&D Public-collab	2.818	4.172	0.000	18.000
R&Dfirm-alliances	0.445	1.017	0.000	8.000
Collab hidf_idf	0.424	0.853	0.000	4.000
Deparure %	1.582	0.987	1.000	4.000
Arrival %	2.745	1.271	1.000	4.000
communication	2.660	0.993	1.000	4.800
institution	1.755	0.890	1.000	5.000
Data bases	2.932	1.257	1.000	5.000
Econ watch hidf	1.064	0.547	0.290	3.889

4.1 Model Specification and Variables

Two dependent variables are used to measure the relative impacts of diffusion mechanisms on innovation and two models are tested. The first one describes a firm's "exploration" strategy in which the dependent variable is the number of patent applications. The second equation describes an "exploitation" strategy based on observing the number of products and processes in the pipeline, which is an indicator of the capacity of the firm to develop its products and processes by looking for partners, markets, etc. (Hall & Bagchi-Sen, 2007; Marsh & Oxley, 2005; Traoré, 2004).

In both cases, the dependent variable is count data available for 60 firms, for 2001 to 2005. We test the knowledge production function Griliches (1979).

$$y_t = x\beta + u_i + \varepsilon_t; \varepsilon_t \sim N(0, \delta^2 I_N)$$

where x is a matrix comprising a set of independent variables which influence the number of patent applications and the number of products and processes in the pipeline of the firm. Two main specifications will be tested. On one hand an exploration model where the number of patent application is considered as the dependent variable. On the other hand, an exploitation model where the total number of R&D projects in the firm's pipeline is used.

4.1.1 The Independent Variables

Firms' R&D activity is defined by the level of their R&D spending¹² (IR&D exp), the number of their R&D collaborations with public research (R&D pub collab), the number of their R&D alliances with firm's partners such as biotech, or pharmaceutical firms (R&D alliances) and the number of their R&D employees. Both types of collaborations can be local as well as national or international. Collaborations are important for supplying and transferring new knowledge and technology as R&D employees are crucial inputs for the innovation activities of firms (IR&D employees)¹³ which are composed of researchers and technicians. Since R&D activities do not yield immediate results, and patent applications can take up to three years, a time lag of q periods is assumed (Verspagen & De Loo, 1999; Fisher & Varga, 2003). We expect R&D spending, R&D collaborations and R&D alliances to have a positive impact on the number of patent applications and products/services in the pipeline.

4.1.2 Control Variables

A set of dummy variables is introduced in the regression to take account of the firm's characteristics such as the age, the specialization, etc. As bigger firms may have more resources to implement their R&D activities and thus may apply for more patents, we control for firm size through a year dummy variable that equals 1 if the company has more than 20 employees. The firm's ability to patent may be influenced by other factors such as specialization in the health industry. We control for firm origin through a dummy variable indicating whether the firm is a university spinoff or has at least one academic founder (Univ spinoff).

4.1.3 Diffusion Mechanisms Variables

In order to test the relevance of the knowledge spillovers mechanisms we introduce the three main factors identified above, which reflect the mechanisms used by companies to access to knowledge and information needed for their innovative activities. These three mechanisms of diffusion are: (1) *Communication* dealing with informal interactions between staff, managers, customers, suppliers, researchers and engineers in symposiums, conferences, and training sessions; (2) *Institutions* supporting firms to achieve their innovative activities by providing key information about financing, partners, markets, etc., and critical other resources through mediation; (3) *Data bases* allowing access to the scientific and technological knowledge and information on the market position of major competitors.

To measure the importance of the regional diffusion mechanisms that facilitates communication between agents we introduce the variable economic watch (Ewatch OIDE/ IDF), where IDF is the total score attributed to the local mechanisms by comparison with the supra regional ones OIDE (the total score attributed to mechanisms outside the region Ile-de-France). A "global chain integration variable" is also introduced indicating whether the firm collaborates with international partners, and showing by the way whether the geographic distance between partners can be an obstacle for collaboration or not. Then the variable (Collab OIDE/IDF) is defined, where Collab OIDE is the total number of collaborations (R&D, production, commercialization) with public and private partners outside the Ile-de-France and CollabIDF is the total number of collaborations with local partners.

Finally in line with the literature, the impact of R&D staff mobility on the diffusion of knowledge within the company and therefore on innovation. We include two variables for departure rate (departure%) and entry rate (entry%) in four years (2000 to 2003). These two variables can take the values of less than 10%, 10-20%, 20-50%, and over 50%. The average for the two variables is 15.8% for departures and 27.4% for arrivals.

¹² This variable is logged to normalize its distribution.

¹³ This variable is logged to normalize its distribution.

4.2 Results and Discussion

4.2.1 Estimation Issues

The two dependent variables used in the regressions are count data positive, with a large number of null values (at least for the variable patent applications). Thus, a Poisson model appears suitable to measure the invention capacity of firms (number of patent applications) and capacity to innovate (total products and processes in the pipeline).

When we look at the distribution of the characteristics of the first dependent variable “number of patent applications” we find that the sample average is 1.48 while the maximum is 20. The dispersion of this distribution is above average (3.24 in our sample), which suggests the use of the negative binomial model (Greene, 2005).

In the case of the dependent variable “number of products and processes”, the average is 4.70 while the maximum is 52. This variable has fewer zeros than the previous one, but over-dispersion of this variable compared to the average suggests the use of a negative binomial as a method of estimation (8.02) (Greene, 2005). The introduction of the parameter “alpha” takes account of the heterogeneity of the dependent variable in the Poisson model. The estimation and significance of this parameter indicates that a negative binomial model is preferred over a Poisson model. In our case, we find that the negative binomial is more appropriate than the Poisson for the estimation of regressions.

First, we test the importance of the diffusion mechanisms in the firms’ exploration model. Three models are tested, a pooled model, a fixed effects model and a random effects model. Regressions with fixed effects control for omitted variables that vary between companies, but are constant over time. The random-effect model controls the omitted variables that vary between companies and are constant over time, and control omitted variables that are constant among firms, but vary over time (Wooldridge, 2002). Then the use of a fixed effects model is recommended in this case because it should provide more robust results. However, this may not be the most efficient model. The Hausman test considers the two models with efficiency as the condition to obtain consistent results. In our case, the random effects model is applied to the exploration regression (patent applications) (table 6), and the fixed effects model is used for the exploitation regression (total products and processes) (table 7).¹⁴

¹⁴ The results of the Hausman test are available on request from the authors.

Table 6. Regression results (negative binomial): diffusion mechanisms in an “*exploration strategy*” model

Model	Pooled		Panel data Random effect	
	(1)		(2)	
Patent	Coefficient	Standard errors	Coefficient	Standard errors
Year	0.314***	0.119		
Spinoff	-0.829***	0.306	-0.537	0.529
Health	0.920**	0.395	0.920**	0.395
Size>20	-0.189	0.381	0.496**	0.259
LR&Dexpend	0.184**	0.072	0.160**	0.071
LR&Demployees	0.128	0.129	0.304	0.202
R&D pub Collab	0.032	0.052	0.156***	0.063
R&D Alliances	-0.365***	0.129	-0.264*	0.150
Collab OIDF IDF	-0.094	0.204	-0.257	0.228
departure %	0.362**	0.165	0.268	0.245
arrival %	-0.226	0.136	-0.294	0.221
Communication	-0.670**	0.219	-0.829*	0.325
Institutions	0.527***	0.160	0.764***	0.291
Databases	0.346**	0.116	0.056	0.197
EcWatch OIDF-IDF	0.209	0.189	-0.141	0.153
_cons	-631.336***	238.927	0.390	1.360
Observations	220		220	
Log-likelihood	-301.361		-270.313	
LR chi2	79.73		31.93	

4.2.2 Firm Capacities

Table 6 presents the results of the regression for the exploration model. If we look at the firm’s level factors explaining innovation we find that R&D expenditure has a positive and significant impact on innovation. For each model, we run pooled and panel regressions stressing the dynamics of firm innovation. In the panel regression six variables are shown to be significant. R&D spending and R&D public collaboration are positive and significant highlighting the strong links between biotechnology firms and public research labs in the Paris region. However, R&D alliances have a negative and significant impact on innovation. This result contrasts with the importance of R&D inter-firm collaborations when a firm is trying to develop its products or to reach new markets (see table 7). This suggests that firms in their early stages of search for new technological and scientific opportunities fear risks and competitors’ opportunistic behaviour. Also, strategic alliances can divert firms from their main targets. However, when activities and products are mature, firms need partnerships to market their products.

Turning to the control variables, in the first model we observe that specialization in human health enhances firms’ capacities to patent, since firms in this sector face “the race for patents” pressure. However, university spin-offs tend to patent less than other firms. This might be because university spin-offs are often created to exploit patents already applied by a university or public research lab. Since these firms are rather young, they are still developing and working on their projects. Another explanation is sometimes invoked to explain the university-spinoffs failure to patent the outcome of their research (often conducted in universities) because the lack of some key managerial competencies (Siegel, Waldman, Atwater & Link, 2003). However, neither the specialization control variable nor the origin variable impacts firm’s capacity to develop products and processes. Finally, only the larger firms (> 20 employees) in the two models present a higher probability to patent or develop products and processes.

Table 7. Regression results (negative binomial): diffusion mechanisms in an “*exploitation strategy*” model

Model	Pooled Model		Panel data Fixed-effect	
	(1)		(2)	
Products and processes in the pipeline	Coefficient	Ecart-type	Coefficient	Ecart-type
Year	0.279***	0.087		
Spinoff	0.129	0.179	-0.085	1.273
Health	-0.339	0.222	1.019	1.084
Size>20	-0.190	0.249	0.276*	0.148
LR&Dexpend	0.135**	0.053	0.153**	0.062
LR&Demployees	0.316***	0.096	0.008	0.170
R&D pub Collab	0.028	0.027	0.165***	0.050
R&D Alliances	0.123*	0.064	-0.176	0.124
Collab OIDEF_IDF	0.294***	0.091	0.337**	0.148
departure %	-0.105	0.096	0.347	0.683
arrival %	-0.024	0.074	-0.474	0.297
Communication	0.070	0.109	-0.689	0.431
Institutions	0.256***	0.090	1.353**	0.565
Databases	-0.225***	0.075	0.061	0.329
EcWatch OIDEF-IDF	-0.313**	0.133	-0.251**	0.124
_cons	-559.177***	173.861	-0.602	1.759
Observations	220		204	
Log-likelihood	-504.566		-262.081	
LR chi2	151.39		87.31	

4.2.3 Diffusion mechanisms

Now let's consider how knowledge and information diffusion mechanisms in “exploration” versus “exploitation” oriented strategies impact innovation. One of the main findings of this study is the role played by institutions as a main channel for knowledge and informational spillovers between agents. Whatever their strategy (exploration or exploitation), and whichever type of model is tested (pooled or panel), the mechanisms described in 3.1 have strong and very significant impacts on the innovation capacity of firms (Proposition 3). The results meet with the conclusions of Champenois (2008). Based on an in-depth qualitative field study reconstructing the founding mechanisms of German biotechnology firms, she demonstrates that successive requirements for resources to build their companies lead founders and managers to stay in the region in which they have been working. Then she concludes that institutional structures (organizations and programs) are more able to give access to the required resources in a less personalized way than through social networks, are a key factor in this respect. A similar study of Barthe, Beslay & Grossetti (2008) in the French case shows that 45% of entrepreneurs appeal to the mediation's resources to mobilize the needed inputs for the creation of their businesses.

Thus, institutional agents provide financial support, material facilities and infrastructure, promote the transfer and the application of scientific knowledge, and enhance networking between firms. Programs and services offered by these agents cover a large stream of firm activities varying from R&D to production and commercialization. For biotech's firms and especially spin-offs, young researchers need help to manage their projects since they may lack managerial competencies to cope with the legal and regulatory frameworks involved in firm creation. For the biotech's firms in the region IDF, the survey shows that the institutional agent the most sought by firms is the chamber of commerce which provide devices and services such as helping entrepreneurs to develop their business plan, diagnosis their capabilities and scan their environment.

Coming to the factor 2, communication as defined by Charlot and Duranton (2004), an unexpected result appears from the regressions. When the importance of informal interactions among agents (suppliers, researchers, entrepreneurs, managers, consultants) as a mechanism of knowledge spillovers is tested, and the question of the geographic patterns of these mechanisms is investigated, the regressions' results show that informal interactions between agents do not necessarily lead to positive knowledge spillovers in the IDF regional cluster.

And in the particular case of an exploration model, communication can reduce the rate of innovation rather than enhancing positive spillovers. Again, this may be explained by the risks involved in the search process, which make firms watchful and careful about revealing key information on their important R&D projects (market opportunities, financing support, and partnerships). Similar to the case of alliances, this suggests that communication could negatively affect the early stage of the R&D process. However, more research is required to establish how many informal channels induce or not knowledge spillovers and thus innovation.

On the third factor, “data bases” as a codified knowledge mechanism diffusion, the results show that their impact depends on whether the firm plans to explore new projects or the exploitation of its results. So when companies are referred to databases to do their business, it seems that the availability of information and knowledge stimulate significantly and positively the probability of firms to patent. This helps firms to keep up-to-date with the latest technological and scientific progress in their field.

However, when it is about the exploitation and the development of their products in the pipeline, the same informational mechanism has rather a negative and a less significant impact. In this case managers may decide to stop and not continue the development of a specific product or service when for example patent databases reveal the hard competition on one market segmentation. Managers prefer to focus on a less risky investment in this case.

The last issue discussed in the paper is on the labour mobility as a conduct for knowledge spillover diffusion. According to the literature presented above, it seems that the turnover of employee between firms can be a good proxy for knowledge spillovers transfer. However, since this indicator is difficult to measure, two alternative indicators were used; the entry rate and the exit rate of R&D employees in one firm during the previous three years. The manager was asked to chose the rate comprised between (less than 10%; (10-20%); (20-50%); more than 50%). Then, the relationship tested in the paper measure the impact of knowledge flows through labour mobility on firm’s capacity to innovate. The results show that theses impacts are minimal but more significant in the case of the exploration model, i.e. when the probability of firms to patent is considered. Two main results can be discussed. First, data collected show that during the period 2000-2003, the inflow of new employees was more important than the outflow (27% vs. 15.8%), however the departure rate of R&D employees during the period impacts positively innovation. Although this result is unexpected based on the findings in the literature, some *sectoral* and *organizational* aspects related to project based firms’ dynamics may explain these findings. According to Hobday (2000) and Brusoni, Prencipe and Salter (1998), high-tech firms are organized around projects and their activities are product-oriented. Thus, organizations such as biotech firms are inherently weak in routine tasks, achieving economies of scale and coordinating cross-project resources. When a project comes forward, achieving its objectives, the team may be restructured according to the needs declined in the new project.

This can lead to the exit of some members of the team. However, at the same time, the end of each business cycle (project-activities) may correspond statistically to scientific or industrial results (patents, products, etc.).

Second, it seems that the inflow rate have no impact on firm’s innovation whatever the model considered is. This result can contrast with the literature dealing with the skilled labour mobility as a main mechanism of knowledge dissemination among firms enabling them to obtain valuable new knowledge and contribute to explain their performance (Almeida & Kogut, 1999). However, some new insights driven by the research of Boschma, Eriksson and Lindgren (2009) suggests that it is not necessarily the mobility of labour that matters in a knowledge diffusion process, but rather the quality of the knowledge brought by new labour inflows (i.e. its compatibility with existing knowledge and competencies in the firm). Based on 101,093 job moves in Swedish plants, these authors show that a portfolio of related competences at firm level increases significantly their growth productivity compared to firms with similar or unrelated competences portfolios’.

Finally, it can be assumed that the institutional and regional mediation plays a very important role in diffusing spillovers in the cluster. It seems that firms’ economic watch is based largely on local sources, even among globalized firms, when they are looking to reach partners to develop and to market their products (see table 7). The strong and positive impact of the non-regional collaboration agreements on one firm product’s pipeline confirms this conclusion.

5. CONCLUSIONS

The aim of the paper was to analyse the mechanisms operating in one regional cluster to diffuse knowledge spillovers between firms. The originality of this paper lies in the fact that the role of these mechanisms is demonstrated, not presupposed as suggested generally in the literature (Breschi & Lissoni, 2001).

Based on a survey of 60 biotech firms co-localized in the Paris Region IDF between 2000 and 2005, two main tasks were performed. First, it was necessary to make a typology of the main mechanisms existing and used by agents to perform their R&D activities. Second, the impact of each main mechanism on the innovation output of one firm was measured by using a knowledge production function (1979).

The results of the empirical analyses highlighted the major role played by the institutional agents and devices as a resource of mediation between firms. This mechanism comparing to labour mobility, codified data bases or informal communication seems, by far, to be the most important mechanism shaping managers' actions by fostering their search capabilities for new business opportunities and R&D possibilities.

These results suggest new insights on the nature of knowledge spillovers. While the literature tends to view externalities as being related to the dissemination of tacit knowledge in limited geographical space, it seems that agents need more established contacts to tap into economic and useful knowledge or information for innovation. Then it can be established in the case of the IDF that informal communication doesn't induce necessarily and spontaneously knowledge exchange between firms. Agents may need more formal conducts to tap into economic and useful knowledge or information.

AUTHOR BIOGRAPHY

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APPENDICIES

Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) patent	1.00							
(2) product_pipeline	0.08 (0.24)	1.00						
(3) age	-0.10 (0.15)	0.37 (0.00)	1.00					
(4) spinoff	-0.21 (0.00)	0.01 (0.93)	-0.27 (0.00)	1.00				
(5) health	0.17 (0.01)	-0.09 (0.21)	-0.30 (0.00)	0.36 (0.00)	1.00			
(6) size>20	-0.02 (0.72)	-0.23 (0.00)	-0.12 (0.08)	-0.02 (0.72)	-0.08 (0.22)	1.00		
(7) L R&D expenditure	0.12 (0.07)	0.33 (0.00)	0.16 (0.02)	0.04 (0.51)	0.25 (0.00)	-0.41 (0.00)	1.00	
(8) L R&D employees	0.11 (0.11)	0.43 (0.00)	-0.05 (0.46)	0.17 (0.01)	0.17 (0.01)	-0.45 (0.00)	0.49 (0.00)	1.00
(9) R&D pub-collab	-0.08 (0.24)	0.27 (0.00)	0.01 (0.83)	0.16 (0.02)	-0.07 (0.28)	-0.20 (0.00)	0.22 (0.00)	0.09 (0.17)
(10) R&D firm- alliances	-0.07 (0.29)	0.20 (0.00)	0.26 (0.00)	0.07 (0.32)	-0.06 (0.35)	-0.02 (0.73)	0.11 (0.10)	0.10 (0.14)
(11) collab hidf_idf	-0.03 (0.65)	0.31 (0.00)	0.22 (0.00)	0.10 (0.14)	0.08 (0.23)	-0.05 (0.48)	0.21 (0.00)	-0.00 (0.99)
(12) departure %	0.03 (0.68)	-0.15 (0.03)	-0.01 (0.86)	-0.02 (0.76)	-0.14 (0.04)	0.26 (0.00)	-0.29 (0.00)	-0.31 (0.00)
(13) arrival %	-0.06 (0.35)	-0.20 (0.00)	-0.23 (0.00)	0.01 (0.85)	0.10 (0.13)	0.19 (0.00)	-0.09 (0.17)	-0.10 (0.13)
(14) communication	-0.08 (0.24)	0.15 (0.02)	-0.10 (0.13)	0.06 (0.36)	-0.07 (0.30)	-0.16 (0.02)	0.15 (0.03)	0.15 (0.03)
(15) institution	0.13 (0.06)	0.07 (0.29)	-0.01 (0.89)	-0.19 (0.00)	-0.10 (0.14)	-0.01 (0.83)	-0.05 (0.45)	0.02
(16) Data bases	0.11 (0.10)	0.01 (0.91)	-0.11 (0.09)	0.01 (0.90)	0.14 (0.04)	-0.04 (0.60)	0.12 (0.07)	0.14
(17) Eco watch_hidf	0.03 (0.61)	-0.04 (0.52)	-0.06 (0.40)	0.04 (0.52)	-0.03 (0.61)	0.15 (0.02)	-0.05 (0.49)	-0.13

(Correlation matrix continued on next page)

(Correlation matrix continued)

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(9) R&D pub-collab	1.00								
(10) R&D firm- alliances	0.39 (0.00)	1.00							
(11) collab hidf_idf	0.54 (0.00)	0.36 (0.00)	1.00						
(12) departure %	-0.04 (0.56)	0.16 (0.02)	-0.12 (0.08)	1.00					
(13) arrival %	-0.14 (0.04)	-0.04 (0.53)	-0.23 (0.00)	0.38 (0.00)	1.00				
(14) communication	0.22 (0.00)	0.01 (0.84)	-0.10 (0.15)	-0.22 (0.00)	-0.16 (0.02)	1.00			
(15) institution	-0.09 (0.19)	-0.02 (0.80)	-0.14 (0.04)	-0.13 (0.05)	-0.20 (0.00)	0.35 (0.00)	1.00		
(16) Data bases	-0.04 (0.56)	0.05 (0.49)	-0.06 (0.36)	-0.03 (0.65)	0.09 (0.16)	0.51 (0.00)	0.24 (0.00)	1.00	
(17) Eco watch_hidf	0.12 (0.07)	0.16 (0.02)	0.06 (0.36)	0.15 (0.03)	0.00 (0.94)	-0.03 (0.68)	0.05 (0.50)	-0.07 (0.29)	1.00